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Short-term household income mobility before and after the Great Recession: A four-country study

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Abstract

This paper analyses short-term intra-generational income mobility in France, Italy, Spain and the UK by exploiting the longitudinal component of EU-SILC for the periods 2005-2008 and 2012-2015. We investigate whether and to what extent the ability of households to move along the income distribution changed after the 2008 crisis and whether heterogeneities among countries exist. For this purpose, we employ mobility indexes and transition matrices as well as estimation of a 2SLS regression and of a dynamic ordered probit with random effects. Overall, indexes and transition matrices point to a decrease of mobility in the aftermath of the crisis. The econometric analyses suggest both the existence of a convergence process of incomes and state dependence of current and lagged income in both periods. We also observe sluggish income convergence and lower upward mobility in the second period. Among the microeconomic drivers, education and employment status are positive determinants of mobility. Finally, our results confirm cross-country heterogeneity.

Keywords: intra-generational income mobility, mobility indexes, 2SLS, dynamic ordered probit, EU-SILC.
JEL classification: C25, C26, D31, J60.

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1. Introduction

With this paper we wish to contribute to the literature by providing a full-fledged analysis of short-term intra-generational income mobility before and after the crisis in selected European countries, as work analysing this aspect is limited. To this end, we exploit the 4-year longitudinal samples of the European Union Survey of Income and Living Conditions (EU-SILC) for the time spans 2005-2008 and 2012-2015 and we focus on household-level data for four of the most relevant countries in Europe: France, Italy, Spain and the UK.[1]

We take our motivation from the fact that the global economic and financial crisis of 2008 severely affected people's economic standing in Europe. Macroeconomic indicators, among which GDP and disposable income, plummeted and on average in the European Union (EU-28, including the UK) regained their 2007 pre-crisis level only in 2014 and 2015, respectively (in some European countries, such as Italy, they have not reached their pre-crisis levels yet). Moreover, the European labour market experienced growing unemployment (it rose from 7.2% in 2007 to the peak of 10.9% in 2013, to go back to 7.6% in 2017), with Spain still having an unemployment rate more than twice as much that of the European average in 2017. In the years following the 2008 crisis, the distribution of incomes became more unequal, especially in the Euro area (the Gini coefficient of the EA-19 rose from 29.4 in 2005 to 30.5 in 2017), despite with different intensity across countries.[2] In addition, subjective indicators such as the consumer confidence index and those measuring the ability to make ends meet displayed downward trends. Overall, despite in some countries we did not observe large swings in inequality, there was a widely held perception that the crisis exposed individuals to increasing vulnerabilities – e.g. higher inequality and diminished opportunities to climb the income ladder – making it harder for them to improve their economic conditions.

In this paper, we are interested in the dynamics of income distribution, that is in whether and by how much household income moves upwards or downwards. We start from the recent work of Aristei and Perugini (2015), Jäntti and Jenkins (2015), Bachmann et al. (2016) and Carroll and Chen (2016) and look at short-term intra-generational income mobility (mobility, for short). We offer an innovative contribution to the literature by testing whether income mobility has changed between the pre- and post-crisis period, as work analysing this aspect is scarce (with the exception of Cantó and Ruiz (2015) for the US and Spain and Kennedy et al. (2015) for Ireland, among others).

At the outset, we provide a preliminary assessment of income mobility by building mobility indexes (Shorrocks, 1978a, 1978b; Fields and Ok, 1996) and transition matrices. While mobility indexes capture the

[1] Unfortunately, data for Germany are not available in EU-SILC.

[2] Unlike in the EA, in the UK the Gini coefficient decreased from 34.6 in 2005 to 33.1 in 2017. In the EU-27, the Gini coefficient fluctuated between 30.6 in 2005 and 31 in 2014 and 2015 (it was 30.7 in 2017).

extent of income volatility, transition matrices inform on the probability of an individual to transition from one quintile to another from one year to the next. Although informative, mobility indexes and transition matrices only provide an aggregate overview of income changes and cannot account for the influence of individual and country-level characteristics that may affect income mobility. For this reason, in the second part of this work, we move to the econometric analysis, which develops along two lines. In the first, we define income mobility as the growth rate of income over a four-year horizon and we assess its determinants and quantify the degree of convergence between last and first year incomes by means of a 2SLS regression in line with Aristei and Perugini (2015). In the second, we estimate the probability that households move between quintiles of the income distribution from one year to the next by using a dynamic ordered probit.

Anticipating our findings, mobility indexes and transition matrices uncover the existence of heterogeneities in income mobility among the countries analysed, with France and Italy displaying the lowest level. All countries, however, experience a reduction in income mobility after 2012. Transition matrices also reveal that in each country the percentage of individuals staying in the same quintile is higher than the percentage of those moving from one quintile to another.

These results are confirmed by the econometric models. In particular, from the 2SLS there is evidence of an income catching-up process in both periods – although of reduced magnitude in the aftermath of the crisis – and of significant heterogeneities among countries. From the dynamic ordered probit we disclose the existence of significant state dependence in both 2005-2008 and 2012-2015. Furthermore, the model unveils that in the post-crisis period it is more difficult to move towards the upper quintile than in the pre-crisis period, particularly for those lying at the bottom of the income distribution. Finally, our empirical strategy allows us to provide insight on the microeconomic drivers of income mobility. We find that both education and the presence of employed family members play an important role in shaping income mobility, although in different magnitude between the two periods. These two drivers may serve as a cushion against the impact of adverse economic conditions on incomes. Significant policy intervention may derive from this evidence with the goal of securing people's economic livelihoods.

The remainder of the article is organized as follows. Section 2 introduces the main papers in the field of income mobility. Section 3 describes the dataset and defines income mobility. In Section 4, we show some stylized facts on income mobility by calculating mobility indexes and transition matrices on EU-SILC data. The two econometric models – 2SLS and dynamic ordered probit – used to estimate mobility and its determinants are presented in Section 5. Section 6 shows and discusses the empirical results and Section 7 concludes with a summary of the main findings.

2. Literature background

The literature on income mobility dates back to Shorrocks (1978a, 1978b) and Fields and Ok (1996) who describe mobility by means of mobility indexes and transition matrices. Subsequent contributions followed and further developed their framework, such as Jarvis and Jenkins (1997, 1998) who employed regression-based methods to estimate longitudinal income variability by population subgroups using the four waves of the British Household Panel Survey (BHPS). Among others, Atkinson et al. (1992) and Jenkins (2000) provide an early discussion on intra-generational income mobility, while Jäntti and Jenkins (2015) a more updated review.[3]

More recently, renewed attention has been placed on mobility indexes. Ayala and Sastre (2008) use the European Community Household Panel (ECHP) to assess differences in the structure of income mobility – also by population subgroups and income sources – in Germany, France, Italy, Spain and the UK. Alves and Martins (2012) build transition matrices using the EU-SILC to study income mobility patterns in Europe between 2005 and 2009. Van Kerm and Pi Alperin (2013) exploit the EU-SILC to describe the intertemporal distribution of income in 26 countries in the pre-crisis period 2003-2007 by calculating income growth indexes, including Field and Ok's mobility measure, capturing the distribution of year-on-year income gains and losses.

Other studies have enriched the analysis by applying econometric models with the aim of dissecting the drivers of mobility. Examples in this direction are Pavlopoulos et al. (2010), who apply a restricted multinomial logit to the ECHP, and Bachmann et al. (2016), who assess income mobility in Europe over the period 2004-2011 with a multinomial logit, despite not making specific reference to possible changes in mobility due to the crisis. This line of research has further evolved to account for state dependence in the income distribution. For instance, Raferzeder and Winter-Ebmer (2007) apply a simple dynamic OLS regression to Austrian administrative data to relate changes in the relative economic position of a worker to personal characteristics. Cappellari (2007) investigates the earnings mobility of low-paid employees in Italy by means of a dynamic four-variate probit model, extending the analytical framework developed by Stewart and Swaffield (1999) for the UK. Aristei and Perugini (2015) define mobility as the percentage change of income between 2004 and 2006 and apply a two-stage least squares (2SLS) model to European data, following the approach of Fields et al. (2003).

[3] Recently, Cowell and Flachaire (2018) introduced a new class of mobility indexes able to distinguish between the issue of movements in terms of status – such as income (as in Cowell, 1985), wealth, social rank, or other criteria – and that of movements between positions (rank mobility). On rank mobility, for instance, see D'Agostino and Dardanoni (2009). However, an empirical application of these approaches is beyond the scope of our paper.

Outside of the European context, examples in the literature are Lamman et al. (2016) who track a sample of Canadians starting in 1993 to measure short- and long-run income changes and Aaberge et al. (2002) and Chen (2009) who make comparisons between North America (the US and Canada) and European countries.

3. The dataset and the definition of income mobility

3.1 The dataset

The dataset used in this paper is from the longitudinal component of European Union Statistics on Income and Living Conditions (EU-SILC) for the two four-year periods 2005-2008 and 2012-2015.[4] The countries analysed are France, Italy, Spain and the UK. EU-SILC is the reference source for comparative statistics on income distribution and social exclusion at European level. It collects information on income, socio-economic characteristics of individuals and households, and qualitative non-monetary variables of deprivation. The reference population is all private households and their current members residing in the territory of the member states at the time of data collection. Its longitudinal sample pertains to individual-level changes over time, observed periodically over a four-year period. Income refers to the previous year, i.e. in the 2005-2008 sample it refers to 2004-2007 and in the 2012-2015 sample it refers to 2011-2014.[5]

For our empirical analysis, we select heads of household aged 16-64 years who have remained part of the survey for all four consecutive years in the two sub-periods 2005-2008 and 2012-2015.[6] This implies that we are working on two balanced panel datasets. The overall number of observations is 70,868, of which 35,508 in 2005-2008 (8,877 households in each year) and 35,360 in 2012-2015 (8,840 households in each year). The composition of the sample is presented in **Table 1**.

TABLE 1 ABOUT HERE

The analysis of income mobility is performed at household level on equivalised household income, a measure traditionally employed in redistributive analysis.[7] Additionally, we want to fully exploit our

[4] Data are made available by Eurostat under project RPP 180/2017-EU-SILC.

[5] In all our analyses, income is brought forward to 2014 by using the consumption deflator.

[6] We identify as heads of household those individuals that earn the highest income within the household in the first year of appearance and follow them thereafter. Noteworthy is that individuals and households belonging to the two panels do not overlap, since the datasets have the structure of rotating panels.

[7] Equivalised income is household disposable income divided by the modified OECD equivalence scale, which assigns the value 1 to the first adult, 0.5 to each other adult and 0.3 to each child under the age of 14.

dataset and cover the whole population following the approach of Jarvis and Jenkins (1997, 1998), Alves and Martins (2012) and van Kerm and Pi Alperin (2013), rather than restricting the analysis to earnings mobility (for instance, as in Aaberge et al., 2002; Raferzeder and Winter-Ebmer, 2007; Pavlopoulos et al., 2010; Bachmann et al., 2015).

3.2 The definition of income mobility

In this paper, we approach income mobility in two different but complementary ways. First, we define income mobility as the degree of income volatility between the first and the last year of the two time spells. Similarly to Aristei and Perugini (2015), the corresponding outcome variable is continuous and equal to the percentage variation of income between the last ($t+3$) and the first year (t) of each sub-period. Second, we characterize income mobility as the probability that each household has of moving, upward or downward, among quintiles of equivalised household income between the current year (t) and the previous one ($t-1$). In this case the outcome variable is ordered and takes values from 1 to 5, according to which income quintile the household belongs at time t. The latter definition is in line with the computation of observed transition matrices of Section 4. The econometric analysis of Section 6 allows for both definitions. We employ a different econometric model according to the outcome variable considered: a 2SLS regression model in the continuous case, and a dynamic ordered probit model in the discrete one.

Table 2 reports 2005-2008 and 2012-2015 descriptive statistics of the variables used in the econometric analysis. We build our variables separately on each of the two sets of data and for each country. Under the 2SLS regression model, the outcome variable is modelled as a function of lagged income, while in the dynamic ordered probit model the outcome variable is modelled as a function of a set of dummy variables, which identify the income quintile in the previous period. Two other groups of controls are employed in each model. One set includes socio-economic characteristics of the household head: age classes, education levels, gender and marital status. Another set comprises household-level variables, namely: the shares on total household components of working members, unemployed, pensioners and adults. Finally, country effects are accounted for by means of dummy variables.

Worthy of note is that average income mobility, defined as the percentage change of equivalised income, drops between the two periods, from 0.032 in 2005-2008 to 0.021 in 2012-2015 and that average log equivalised income decreases from 9.850 to 9.823 (**Table 2**).

TABLE 2 ABOUT HERE

4. Mobility indexes and transition matrices

At the outset, we make use of mobility measures to provide a preliminary description of the degree of income mobility observed in our data. Although the literature supplies several alternative indexes, we settle for the Fields and Ok (1996 and 1999) (*FO*) index and the Shorrocks (1978a, 1978b) (*M*) index, as they have been widely used in the related literature thus allowing us to make comparisons between our results and those obtained by similar studies.

The *FO* index is calculated as follows:

$$FO_n(x, y) = \frac{1}{n}\sum_{i=1}^{n}|\ln x_i - \ln y_i| = \frac{1}{n}\sum_{i=1}^{n} d(x_i, y_i) \tag{1}$$

where n is the number of individuals, x and y are the vectors of the initial (t) and final distributions of income ($t + 3$), respectively. $d(x_i, y_i)$ is the "non-directional" growth of individual incomes. As such, the *FO* summarises the degree of variation in individual incomes regardless of their direction and, by definition, it takes up a minimum value of 0 in the extreme case of perfect immobility.

A useful feature of the *FO* index is that it additively disaggregates into two components, one attributable to growth and one to transfer of incomes (Fields and Ok, 1999).[8] In particular, the *FO* index for a growing economy can be written as:[9]

$$FO_n(x, y) = G(x, y) + T(x, y) = \frac{1}{n}\sum_{i=1}^{N}(lny_i - lnx_i) + \frac{2}{n}\sum_{i \in L}(lnx_i - lny_i) \tag{2}$$

where $G(x, y)$ is the growth component and $T(x, y)$ is the transfer one. Worthy of note is that the growth component is Fields and Ok's directional measure. If positive, total income movements are welfare increasing, while negative values represent a shrinking economy (one where incomes fall on average) (Burkhauser and Couch, 2009).

Alternatively, we consider Shorrocks' *M* index:

$$M(T) = 1 - I[Y(T)] / \sum_{t=1}^{T} \frac{\mu_t}{\mu} I(Y_t) \tag{3}$$

where $I[Y(T)]$ and $I(Y_t)$ indicate inequality calculated on the average income over period T and in each period t, respectively, while μ and μ_t are the corresponding income averages. An *M* index equal to 0 indicates

[8] Unlike generalised entropy inequality measures, mobility indexes cannot be decomposed into within- and between-group terms.

[9] A similar decomposition holds for a shrinking economy (Fields and Ok, 1999).

a situation of perfect immobility, and an *M* index of 1 a case of perfect mobility. The *M* index allows us to associate mobility to the evolution of inequality.[10] The main idea is that income mobility rises (decreases) because of the reduction (increase) of inequality over time due to the movement (immobility) of individuals along the income distribution.[11] The *M* index can be computed using a wide variety of mean-independent inequality measures, thereby allowing us to put more weight on specific parts of the income distribution.

Table 3 reports mobility measures by country and period of analysis. On average, both the *FO* and *M* index show that in the years prior to the crisis (period 1 = 2005-2008), Spain experiences the highest levels of income mobility followed by the UK, Italy and France. This ranking is comparable to that found in Aristei and Perugini (2015) for the period 2004-2006.

TABLE 3 ABOUT HERE

Decomposition of the *FO* index reveals that the transfer component contributes the most to overall income mobility. Income movements are mostly due to transfer of incomes from losers (those whose income falls) to gainers rather than due to income growth. Noteworthy is that the growth component is negative for the UK, indicating that on average incomes in the country have declined. As regards the post-crisis period (period 2 = 2012-2015), mobility decreases for all countries, especially for Spain. Nevertheless, country rankings are maintained. Again, income mobility is mostly due to transfer of incomes. The growth component turns positive for the UK but negative for Italy and Spain.

Focusing on the *M* index, we observe that it varies according to the type of inequality measure employed in Eq. 2. When using the Gini coefficient, which puts more weight on the middle of the income distribution, income mobility is lower than when using the class of General Entropy (GE) indexes, namely mean log deviation (GE(0)), Theil (GE(1)) and the squared of the coefficient of variation (GE(2)), which put more weight on the tails of the distribution. In other words, income mobility at the tails of the income distribution is greater compared to that in the middle. This finding is consistent with that of Sologon and

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[10] Some papers study the relationship between mobility and inequality (see, among others, Gardiner and Hills, 1999; Burkhauser and Couch, 2009; Fields, 2010; Prieto-Rodriguez et al., 2010; van Kerm and Pi Alperin, 2013; OECD, 2015; Garnero et al., 2019). For instance, Fields (2010) finds that higher mobility can even out income inequality in the long-term as individuals have more opportunities to move up the income ladder. Prieto-Rodriguez et al. (2010) and Garnero et al. (2019) suggest that a society with higher income mobility can perceive income inequalities as more acceptable thus reducing the desire for redistribution. However, studying the relationship between mobility and inequality is beyond the scope of this paper.

[11] To be more precise, the *M* index reflects the proportional contribution of permanent ($I[Y(T)]$) to total income inequality ($I(Y_t)$): if the former is smoothed out in the long-run, the income distribution is more mobile.

O'Donogue (2009) who find that in Europe people at the top of the distribution are more mobile than people at the bottom, which in turn are more mobile than people in the middle.

Despite their informative value, mobility indexes can provide only an aggregate overview of income changes and they are not designed to inform on what actually happens along the income distribution, i.e. where do individuals move from and to where. To gauge movements along the income distribution we exploit transition matrices, which associate income group destinations with income group origins. In our case, income groups are represented by quintiles. **Panels (a-h)** in **Table 4** show annual transition matrices by country and period. Each cell represents the number of times (in percentage) that individuals stay in the same quintile (main diagonal), move upwards (upper triangle of the matrix) or downwards (lower triangle of the matrix).

A number of general considerations emerge. First, over the pre-crisis period we observe a high concentration of individuals staying in the same quintile, especially at the tails of the distribution. Similar considerations apply in the post-crisis period, although the percentages are slightly higher. This evidence of lower mobility at the tails of the distribution is in contrast to the indications provided by the *M* index above. Notwithstanding, there is evidence of the high persistence of incomes at the lower end of the income distribution.[12] However, the fact that income mobility appears to be lower in the second period perfectly reflects the reduction in both the *FO* and *M* indexes seen earlier on. Second, short-distance mobility is more common than long-distance mobility. **Panel (e)** in **Table 4**, for example, shows that in Spain over the period 2005-2008 half of the poorest fifth in one year are no longer in the poorest fifth (22.1 + 10.3 + 4.7 + 1.4) in the next year, although more than half of these leavers move only to the next two quintiles (22.1 + 10.3).

TABLE 4 ABOUT HERE

We re-elaborate and summarise the information provided by the income matrices in **Figure 1**, where we report the percentage of individuals staying in the same quintile, moving upward or downward across quintiles.[13] It emerges that, overall, income mobility decreases from period 1 to period 2 as the percentages of individuals staying in the same quintile increase. Accordingly, both downward and upward mobility are lower in 2012-2015. Furthermore, in Italy and France the reduction of upward mobility is greater than that of downward mobility.

[12] See, for example, Cappellari and Jenkins (2014).

[13] To calculate these percentages, we add the number of households in the diagonal (Stay), in the lower triangle (Down) and upper triangle (Up) of each of the transition matrix and divide them for the total number of households included in the sample.

FIGURE 1 ABOUT HERE

Overall, the main takeaways from this descriptive analysis are the following. First, there are systematic differences in income mobility between France, Italy, Spain and the UK. In the aftermath of the crisis, the income distribution turns out to be less mobile for all countries, especially in Spain, which experiences the greatest reduction in income mobility. Second, there is some preliminary evidence of the high persistence of incomes at the tails of the income distribution, both across space and time. Last, but not least, short-distance mobility is much more common than long-distance mobility.

5. Econometric analysis: Determinants and dynamics of income mobility

The descriptive analysis develops along two lines. On the one hand, mobility is measured by means of mobility indexes, which are a synthetic measure of income volatility and inform on by how much incomes fluctuate. On the other hand, mobility is assessed by means of transition matrices, which allow us to disentangle some of the unresolved issues put forth by mobility indexes. Specifically, they inform about movements along the income distribution. Both approaches are informative and complement each other. They both suggest that differences exist in short-term income mobility among countries and through time. We take this preliminary evidence as the basis for our econometric analysis, which aims at unravelling the effects of past income, time factors, countries' specificities, as well as household socio-economic characteristics on mobility.

Our econometric analysis mirrors the two approaches. By analogy with mobility indexes, we take the percentage variation of household income as the outcome variable of a two-stage least squares (2SLS) regression to relate income volatility to initial-year income, household characteristics and country effects. By analogy with transition matrices, we take the position of each household along the income distribution – i.e. the income quintile they belong to – to relate income movements to previous state, household characteristics and country effects, by means of a dynamic ordered probit (Wooldridge, 2005).

Both estimation methods are applied to the EU-SILC four-year balanced panel datasets for France, Italy, Spain and the UK covering the two periods 2005-2008 and 2012-2015.[14] For both models, we estimate

[14] We are aware that restricting the analysis to the balanced panel component may introduce attrition problems. However, we feel we are constrained to this choice mainly for two reasons. First, in the 2SLS model we wish to estimate mobility on the longest possible spell and at the same time include the start and the end of both periods. Second, in the dynamic ordered probit we need the maximum available time periods since (i) by introducing the lagged outcome variable among the regressors we lose one period and (ii) the model structure requires to distinguish between current values and time averages.

four specifications: (i) pooling of the two sub-samples 2005-2008 and 2012-2015 with a dummy identifying the post-crisis period (Model 1), (ii) pooling of the two samples augmented with the interactions between country dummies and the second period dummy (Model 2), (iii) 2005-2008 only (Model 3) and finally (iv) 2012-2015 only (Model 4). The idea is to gauge whether income mobility patterns have changed from the pre-crisis to the post-crisis period.

5.1 A two-stage least square regression model

We build our first model by taking from Fields et al. (2003) and Aristei and Perugini (2015). In both papers, the authors define income mobility as the percentage variation of income between the last and the first year of their samples, 1998 and 1993 in the former, and 2006 and 2004 in the latter. In our case, we model income mobility as the difference between log equivalised income of the final year and log equivalised income of the initial year for both sub-periods 2005-2008 (T_1) and 2012-2015 (T_2) for each household $i = (1, \dots, N_1; 1, \dots, N_2)$. This definition of income mobility corresponds to the growth component of the *FO* index of Eq. 2.[15] It implies a change in the data structure, i.e. the two longitudinal datasets collapse into two cross-sections that capture the changes in income over the period 2005-2008 and 2012-2015, respectively.

The percentage variation of income is estimated as a function of initial year log equivalised income, a set of initial year regressors, a set of variables in percentage change, a period dummy and country dummies. Formally, income mobility is modelled as follows:[16]

$$\Delta \ln y_i = lny_{i,t} - lny_{i,t-3} = f\left[\ln y_{i,t-3}, X_{i,t-3}, \Delta W_i, T_{i,t-3}, C_{i,t-3}, \varepsilon_{i,t-3}, \Delta\varepsilon_i\right] \quad (3)$$

In Eq. 3, $\Delta \ln y_i$ is a measure of income mobility calculated as the percentage variation in real terms of the equivalised income between t and $t-3$ ($lny_{i,t} - lny_{i,t-3}$), where $\ln y_{i,t-3}$ is the logarithm of equivalised income at time $t-3$ and $lny_{i,t}$ is the logarithm of equivalised income at time t.[17] $X_{i,t-3}$ is a set of household head (age classes, education levels, gender and marital status) and household level characteristics (the share of working members, the share of unemployed and the share of pensioners within the household) at time $t-3$. ΔW_i includes the above household-level characteristics (to which we add the percentage of adults)

[15] Other authors use the coefficient of variation as a measure of income mobility (e.g. Raferzeder and Winter-Ebmer, 2007; Beccaria et al., 2016).

[16] A formal derivation of the model can be found in Aristei and Perugini (2015).

[17] In our framework, $t-3$ identifies the initial year of each of the two sub-periods, i.e. 2005 and 2012 respectively, while t identifies the final year of each sub-period, i.e. 2008 and 2015 respectively.

expressed as difference between the last and the first year of each sub-period. Finally, to disentangle the country effects and to gain some insight on the consequences of the crisis on income mobility, the model also contains country-specific $C_{i,t-3}$ dummy variables and, in the pooled specifications, a dummy variable that identifies the post-crisis period, $T_{i,t-3}$ (Model 1) and the interactions between country and post-crisis dummies (Model 2).

To account for the potential endogeneity bias deriving from the inclusion of lagged income among the covariates and to solve the measurement error issue, we estimate Eq. 3 within an instrumental variable (IV) framework and run a first-stage regression that predicts the value of first year income, $\ln y_{i,t-3}$:[18]

$$\ln y_{i,t-3} = f\left[Z_{i,t-3}, \Delta W_i, T_{i,t-3}, C_{i,t-3}, \varepsilon_{i,t-3}, \Delta\varepsilon_i\right] \tag{4}$$

where $Z_{i,t-3}$ includes the set of regressors $X_{i,t-3}$ of Eq. 3 and the instrument $z_{i,t-3}$. In a dynamic setting, the ideal IV would be a variable able to express pre-sample information to explain income levels in the initial period. However, the EU-SILC does not contain any of these variables. Following Fields et al. (2003) and Aristei and Perugini (2015) we employ financial asset ownership as instrument, as it is reasonable to assume that in the initial period richer households are more likely to make investments. To avoid correlation between asset ownership and our dependent variable ($\Delta \ln y_i$), we exclude capital gains from income.[19]

5.2 A dynamic ordered probit model

As a second model, we implement a dynamic ordered probit with random effects in the four specifications introduced above (Model 1 to Model 4). The dependent variable q_{it} is ordinal and is given a value from 1 to 5, according to the quintile to which each household's equivalised income belongs. Inclusion of income quintiles of the previous year in the regressors' set allows us to quantify the degree of state dependence.[20]

The latent variable specification of our model – that holds for both periods T_1 and T_2 and for the pooling specifications – is the following:

[18] A potential candidate to estimate a linear dynamic model is the system GMM (Generalised Method of Moments) estimator. We do not employ it for two reasons. First, in line with mobility indexes, we are interested in overall mobility, i.e. between the last and the first year of the period, and therefore our model reduces to a 2-period setting. Second, even if we were to look at annual mobility, the method would suffer from the drawback that explicit fixed-effects (i.e. country dummies) could not be included among the regressors especially when T is small, as in our case (Roodman, 2009).

[19] Our main insights do not change when we estimate the model on original income. Results are available upon request.

[20] Contoyannis et al. (2004) apply the same methodology to the dynamics of health in the UK.

$$q_{it}^* = \beta' x_{it} + \gamma' q_{it-1} + \alpha_i + u_{it} \qquad (i = 1, \dots, N; t = 2, \dots, T) \qquad (5)$$

where x_{it} is a set of observed variables which are thought to affect each household's position along the income distribution, q_{it-1} is a set of four (out of five) indicator variables that identify in which income quintile household i falls in the previous year and parameters γ are associated with state dependence. Unobserved heterogeneity is captured by the household-specific and time-invariant random component α_i, while u_{it} is a normally distributed random term, uncorrelated across households and time and uncorrelated with unobserved heterogeneity. Moreover, u_{it} is strictly exogenous.

The observed value of the outcome variable q_{it} is determined by q_{it}^* falling into a particular interval, that is:

$$\begin{aligned} &q_{it} = 1 \; if \; q_{it}^* \le \mu_1 \\ &q_{it} = 2 \; if \; \mu_1 < q_{it}^* \le \mu_2 \qquad (6) \\ &\dots \\ &\dots \\ &q_{it} = 5 \; if \; q_{it}^* > \mu_4 \end{aligned}$$

where the cut points μ are parameters to be estimated alongside with the β and γ of Eq. 5. Given the standard normal assumption of the error term u_{it}, the probability of observing the income quintile *j* in which household *i* falls at time *t* is given by:

$$P_{itj} = P(q_{it} = j | x_{it}, q_{it-1}) = \Phi\left(\frac{\mu_j}{\sqrt{1+\sigma_\alpha^2}} - \frac{\beta' x_{it} + \gamma' q_{it-1}}{\sqrt{1+\sigma_\alpha^2}}\right) - \Phi\left(\frac{\mu_{j-1}}{\sqrt{1+\sigma_\alpha^2}} - \frac{\beta' x_{it} + \gamma' q_{it-1}}{\sqrt{1+\sigma_\alpha^2}}\right) \qquad (7)$$

where $\Phi(.)$ is the standard normal distribution function and σ_α^2 is the variance of the individual effects α_i (Greene and Hensher, 2010).[21] As standard in the literature, we have normalised the constant term (β_0) of Eq. 5 to 0, since it is not possible to separately identify the intercept and the cut points.

Estimation of the random effects dynamic model of Eq. 5 requires taking into account two issues: the presence of the time-invariant unobserved heterogeneity α_i and of the lagged outcome variable q_{it-1} among the regressors. Neglecting the former causes the estimate of state dependence to be spurious, therefore overestimating true state dependence. Neglecting the latter (the so-called initial conditions problem) is equivalent to assuming that the previous state is an exogenous variable and, therefore, that the observed start of the stochastic process coincides with the true start of the process. The literature has

[21] Eq. 7 reduces to $P_{it1} = P(q_{it} = 1) = \Phi\left(\frac{\mu_1}{\sqrt{1+\sigma_\alpha^2}} - \frac{\beta' x_{it} + \gamma' q_{it-1}}{\sqrt{1+\sigma_\alpha^2}}\right)$ and $P_{it5} = P(q_{it} = 5) = 1 - \Phi\left(\frac{\mu_4}{\sqrt{1+\sigma_\alpha^2}} - \frac{\beta' x_{it} + \gamma' q_{it-1}}{\sqrt{1+\sigma_\alpha^2}}\right)$ for the first and last quintile, respectively.

extensively investigated the issue, from Heckman (1981) to Wooldridge (2005) and Arulampalam and Stewart (2009). We follow Wooldridge's (2005) methodology, which is well suited to estimating any non-linear dynamic random effects model. It solves the initial conditions problem and accounts for individual effects therefore avoiding spurious state dependence. Wooldridge's is a conditional maximum likelihood approach that models the distribution of the unobserved individual effects conditional on the initial value and the exogenous regressors. It is of straightforward implementation since it only requires modelling unobserved heterogeneity α_i of Eq. 5 as follows:

$$\alpha_i = \alpha_0 + \alpha_1' q_{i1} + \alpha_2' \overline{x}_i + \zeta_i \tag{8}$$

where q_{i1} is the set of four (out of the five categories of our ordered outcome variable) indicator variables in the initial period ($t = 1$) and $\overline{x}_i$ is the average over time of the time-varying exogenous variables excluding the initial-period value (Rabe-Hesketh and Skrondal, 2013). Therefore, replacing α_i of Eq. 5 with α_i of Eq. 8 gives:

$$q_{it}^* = \beta' x_{it} + \gamma' q_{it-1} + \alpha_0 + \alpha_1' q_{i1} + \alpha_2' \overline{x}_i + \zeta_i + u_{it} \quad (i = 1, \dots, N; t = 2, \dots, T) \tag{9}$$

Our specification models the current position in the income distribution, q_{it}, as a function of four indicator variables of the position in the income distribution in the previous state, i.e. whether the household belongs to quintile 1, quintile 2, quintile 4 or quintile 5 at time $t - 1$. We choose quintile 3 at time $t - 1$ as our baseline category. The other explanatory variables are the same as those employed in the 2SLS model. Household and household-head characteristics are taken at time $t - 1$ as it is reasonable to assume that income mobility is influenced by past characteristics. The model specification also includes within-household averages of time-varying explanatory variables.

6. The empirical results

We recall that we estimate four specifications of both the 2SLS model and the dynamic ordered probit one. They are: (i) pooling of the two sub-samples 2005-2008 and 2012-2015 with a dummy identifying the post-crisis period (Model 1), (ii) pooling of the two datasets as in (i) augmented with the interactions between country dummies and the second period dummy (Model 2), (iii) 2005-2008 only (Model 3) and finally (iv) 2012-2015 only (Model 4).

As for the variables employed, in addition to the lagged outcome variable, we have:

a) Household head characteristics (all variables are lagged): dummies capturing the age group the individual falls into (16-34, 35-44, 45-54 and 55-64, with 35-44 as the baseline category), dummies representing the education level (no title or primary, lower secondary, upper secondary and post-secondary or tertiary, with lower secondary as the reference), gender (male/female, where male is the reference category) and marital status (married/other, with other as baseline);
b) Household characteristics (all variables in lag and in first difference): the shares to total household components of the number of workers, unemployed and pensioners, and the ratio of number of adults to total components (only in first difference);
c) Country dummies (France, Italy, Spain and UK, with Italy as the baseline category).

In the pooled models, we also include:

d) Time: a post-crisis dummy that takes the value 1 in the second period and the value 0 in the first;
e) Interactions (only in Model 2): country dummies multiplied by the post-crisis dummy.

6.1 The estimated coefficients of the 2SLS model

Table 5 displays the estimation results of the four IV regression specifications.[22] In all models, the validity of the 2SLS model is confirmed by the tests reported at the bottom of the table. The Wu-Hausman endogeneity test does not accept the null hypothesis of exogeneity of lagged income, thus supporting the use of an IV approach. Additionally, we do not accept the null of the Kleibergen-Paap weak identification test, thus supporting the use of financial asset ownership as an appropriate instrument for lagged income.

TABLE 5 ABOUT HERE

In all the four models, the estimate of the main parameter of interest – the coefficient of lagged income – is significantly different from zero and negatively related to income growth, implying that income follows a convergence trend. This result is in line with that of Aristei and Perugini (2015) for Europe and that of Fields et al. (2003 and 2015) for extra-European countries.

As regards Model (1), the value of the lagged income coefficient is -0.238. Estimation of the model reveals significant time and country effects. The dummy variable that identifies period 2012-2015 is negative (-0.005), although not significant, signalling a weak similarity with the evidence obtained from mobility indexes. The significance of the country effects confirms the evidence of heterogeneities found in former empirical studies (see, for instance, Ayala and Sastre, 2008; Aristei and Perugini, 2015). The coefficients of all country dummies are positive, signalling higher mobility in France, Spain and the UK with respect to Italy.

[22] The first-stage regression results are displayed in **Table A1** of the Appendix.

As for the household head characteristics, income mobility is higher for all age groups than for the reference category (35-44), a result that is counterintuitive especially for the 55-64 class, since we would expect their incomes to be more stable than those of the 35-44 age group. However, the 55-64 class coefficient (0.022) is smaller than the 16-34 age class one (0.032) and this result may suggest that, as Ayala and Sastre (2008) point out, higher stability of older workers' incomes implies lower mobility for this group than for younger workers. Educational attainment positively affects income mobility at an increasing pace for higher education levels. This may be interpreted as a sign of greater opportunities for more highly educated workers to climb the income ladder – in case of positive income changes – but also to allow them to smooth income changes in case of negative income growth. Finally, we do not observe either a significant gender effect or a marital status one on income mobility.

Among the household-level variables, as expected, a larger share of unemployed transmits a negative impulse to income mobility. At the opposite, a larger share of workers within the family unit boosts income growth and prevents equivalised income from experiencing negative swings. The share of pensioners is also significant and positive. Household-level variables in first difference grasp the impact of variations in household composition on income mobility. Their signs and significance are in line with those of the corresponding lagged variables: an increase in the share of workers and in that of pensioners brings about greater mobility, while an increase in the share of unemployed household members causes income mobility to decrease. Among the first difference variables, we include the share of adults to account for changes in household composition, in addition to controlling for household composition by using equivalised income. Its sign is positive, suggesting a higher volatility of incomes.

Table 5 also displays an augmented version of the IV model, in which we interact the country effects with time to evaluate the dynamics of income mobility across both time and space (Model 2). The general results still hold in terms of both sign and significance of the coefficients. We detect a reduction, in absolute value, of the coefficient of initial year income, which now equals -0.169. The second period dummy is now significantly negative, confirming the reduction in mobility provided by all mobility indexes in **Table 3**. The coefficients associated with the country dummies are positive for France and negative for Spain and the UK. This result is coherent with the evidence provided by the growth component of the *FO* index of **Table 3**. The joint impact of the country dummies and their interaction with the time dummy tells us that in period 2 mobility, relative to that in Italy, is higher in the UK (-0.106 + 0.308 = 0.202), followed by Spain (-0.013 + 0.106 = 0.093) and France (0.078 + 0.071 = 0.149). With the exception of Spain, there is coherence with the *FO* index growth component.

When estimating the 2SLS model on the two separate periods (Model 3 and Model 4), we observe the same general results as for the pooled models, despite a lower degree of significance for some variables in period 2. Specifically, among the household head characteristics, age and education turn out to be less relevant determinants of income mobility. In both periods the share of pensioners loses their significance, while its first difference retains its role in the second period only. As for initial year income, the negative sign of the coefficient in both periods confirms the existence of a convergence process of income levels within each period. Its magnitude signals that the catching-up process is slower in the 2012-2015 period than in the 2005-2008 one, since the value of the coefficient drops, in absolute value, from 0.235 in period 1 to 0.110 in period 2. Again, the sign and magnitude of the country dummies are consistent with what found in Model 2 and with the evidence provided by the growth component of the *FO* index.

To sum up, the results of the 2SLS models provide evidence of: (i) systematic differences in income mobility between the countries analysed, with Italy experiencing the lowest level of income mobility of all, (ii) lower mobility in the aftermath of the crisis, and (iii) the existence of a catching-up process in both periods, with evidence of a slower one in the post-crisis period. Regarding socio-economic characteristics, income mobility is positively related to education and the share of workers within the household, while it is negatively affected by the presence of unemployed household members.

6.2 *The estimated average partial effects of the dynamic ordered probit*

From the estimation of Eq. 9, we calculate the average partial effects (APEs) of the regressors for each outcome $q_{it} = 1, \dots, 5$.[23] The APEs inform on by how much the probability of falling in any outcome changes when a regressor changes by one unit and provide an indication of the magnitude of the associations between income quintiles and the regressors.[24] For the sake of brevity, **Table 6** shows only the APEs on the probability of being in quintile 5 in year t for all models and their statistical significance.[25] The APEs of the

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[23] Average partial effects of a dichotomic variable are computed by taking differences in probabilities of Eq. 7 when the variable takes value 1 and when it takes value 0 for each individual and averaging the computed values over the sample population. When a variable is continuous, APEs are the partial derivatives of probabilities, averaged over the population, and they capture the effect of an instantaneous change on the probability of a specific outcome.

[24] In **Table A2** of the Appendix, we report the related coefficient estimates, which only have a qualitative interpretation and do not provide the magnitude of the associations between the outcome variable and the regressors. In all models, the tests of joint significance do not accept the null of the initial conditions and within time average variables coefficients being jointly equal to zero, thus suggesting the appropriateness of applying a dynamic correlated random effects model. Furthermore, the estimated coefficients on the one-year lags of the income quintiles are highly statistically significant. This provides an indication of existing state dependence of incomes along the income distribution, i.e. where income falls along the income distribution in the previous year influences in which quintile income falls in the next.

[25] The APEs on the probability of being in quintile 1 would be the same but opposite in sign. The APEs for the outcomes $q_{it} = 1, 2, 3, 4$ are available from the authors upon request.

previous state income quintiles quantify by how much it is more (when the sign is positive) or less (when the sign is negative) likely to move towards the highest quintile from quintile 1, 2, or 4 than from the third (the reference category).

TABLE 6 ABOUT HERE

In all four models our results (**Table 6**) suggest that the lower a household is in the income distribution, the more difficult it is for it to end at the top of the distribution. More specifically, while it is more difficult to climb the income ladder for households in quintile 1 and 2 with respect to those in quintile 3, it is more likely for households in the fourth quintile to move upwards. Households in the fifth quintile are more likely to remain where they are. This is in line with the evidence emerging from the transition matrices of **Table 4**. Overall, the percentage of households arriving to quintile 5 is greater for households that begin higher in the income distribution.

Focusing on Model (1), the estimation delivers significant country effects, although limited to France and the UK. The APEs of the corresponding country dummies are negative. For French and British households the probability of belonging to income quintile 5 is lower – by 2.0pp and 2.6pp, respectively – than that of an individual living in Italy (the reference category). However, there is no evidence of time effects as the dummy variable that identifies the 2012-2015 period is not significant.

Regarding the household head characteristics, older individuals are more likely to be in quintile 5. It also emerges that education significantly affects the likelihood of households to be in top income quintile. In particular, the probability of being in the upper quintile increases with the level of education. The likelihood of households whose head holds no or primary education to be in income quintile 5 decreases by 1.5pp, while it increases by 7.3pp for an individual living in a household where the head possesses a post-secondary or tertiary education, compared to an individual whose household head with a lower secondary education (the reference category).

Among the household characteristics, the probability of households to lie in income quintile 5 significantly increases with the share of workers in the family unit. A larger share of unemployed and pensioners makes it less probable for households to be at the top, although this effect is not significant.

Model (2) of **Table 6** is an augmented version of the previous model. To the set of country and period dummies we add their interaction to capture if the probability of being in the upper part of the income distribution varies both across time and space. The overall results are in line with the previous ones in terms of both significance and magnitude of the APEs. Nevertheless, the inclusion of the interaction terms discloses that in period 2 households located in Spain have a higher probability – by 1.8pp – of being in the upper quintile than Italian households. For France and the UK the APEs are not significant. To draw a parallel to the transition matrices of **Table 4**, the percentage of households starting from income quintile 5 at t -1 and belonging to 5 at t in period 2 is higher in Spain than in Italy (see **Table 4,** panels d and f). We do not observe relevant differences between Italy, France and the UK (**Table 4,** panels b, d and h).

The dynamic ordered probit model estimated on the two periods separately (Model 3 and 4) yields largely the same results. The only exception regards the dummy for no or primary education, which loses its statistical relevance in period 2. Moreover, there is a sizeable reduction in the APEs for the dummy for upper secondary and tertiary education. This result may suggest that the crisis hit transversally the whole of the population, regardless of their educational attainment, but having a higher education helped households limit its negative impact on their incomes.

Worthy of note is the change in the APEs associated with the previous state income quintiles. For households in quintile 1 and 2, the APE associated with moving to quintile 5, compared to that of households in quintile 3, is smaller in period 2. Conversely, for households in quintile 4 the APE increases from 2.9pp to 3.1pp, while that for households in quintile 5 increases from 8.9pp to 9.9pp. These results suggest that, in the aftermath of the crisis, compared to the pre-crisis years, households lying at the bottom of the income distribution experience greater comparative difficulty in moving upwards. Those households lying in the upper part of the distribution do not face this increased difficulty in the post-crisis period, but in fact have an increase in the likelihood of improving their economic standing versus those in the middle and lower income brackets.

In order to have a broader picture of our estimated effects, we calculate the predicted probabilities of moving in quintile 1 to 5 at time t for each level of education as well as for the share of employed household members. We do this for the reference household (where the household head is a male between 35-44 years of age, married, belonging to quintile 3 at time t - 1), for each period separately and by holding factor variables at their baseline category and continuous variables at their means.[26] A drawback of this exercise is that the computed predicted probabilities pertain only to the reference household. However, it is the most convenient way to show the likelihood for households of moving into each of the five outcomes depending on the head's educational level and the ratio of workers within the family.

Figure 2 shows predicted probabilities for each level of education calculated for the sample 2005-2008 (**panel a**) and 2012-2015 (**panel b**). Noteworthy are the lower values of probabilities across all levels of schooling, except for those associated with moving into quintile 1 and 5 at time t. In other words, for the baseline household the probabilities of moving into the lower and upper quintile at time t are higher in the post-crisis period than in the pre-crisis one, while those of moving into the remaining quantiles are lower.

[26] When estimating predicted probabilities for the share of employed family members, the reference household is also one where the head holds a lower secondary education.

However, a closer look at the predicted probabilities within each outcome reveals that when the household head holds no or primary education, the predicted probability of moving into quintile 1 at time *t* increases by 50% from the pre-crisis period to the post-crisis one. For households where the head holds a tertiary education this probability increases only by 43%. Similarly, the chances of moving into the upper quintile at time *t* for households where the head holds no or primary education increase by only 38.6% between 2005-2008 and 2012-2015. But they increase by 53% when the household head holds a tertiary degree.

FIGURE 2 ABOUT HERE

Figure 3 plots predicted probabilities by the share of employed household components for the pre-crisis (**panel a**) and the post-crisis (**panel b**) periods. Within each time spell, it is clear that the higher the ratio of workers within the family unit, the higher the likelihood for households to move into the upper quintiles at time *t* but the lower their chances to move into the lower quintiles. A comparison between periods shows that the probabilities of moving into quintile 1 and 5 at time *t* are lower in 2012-2015 compared to 2005-2008. However, those associated to the other outcomes slightly increase.

FIGURE 3 ABOUT HERE

Wrapping up, the following insights emerge from the results of the dynamic ordered probit model. First, there is significant evidence of state dependence of incomes along the income distribution. In particular, households at the lower end of the distribution are less likely to move upwards than those lying at the top. More importantly, this effect is greater in the aftermath of the crisis. Second, we find evidence of heterogeneities across countries and time. Prior to and after the crisis, the probability for French and British households to be in income quintile 5 is lower than that for Italian households. In Spain, households are more likely to be at the top in period 2 compared to Italian ones. Third, the effect of education on households falling in quintile 5 is larger for higher levels of educational attainment of the household head. Finally, a larger share of workers exerts a positive impact on the likelihood of households to lie in the upper part of the income distribution.

7. Conclusions

In this paper, we fill in the gap of the literature on intra-generational income mobility since there is a shortage of analysis on whether and by how much income mobility has changed in the aftermath of the Great Recession. We give our contribution by exploiting the longitudinal samples of EU-SILC data on the periods 2005-2008 and 2012-2015 for France, Italy, Spain and the UK. We perform a three-level analysis:

computation of mobility indexes, inspection of transition matrices and econometric investigation of income mobility. The econometric analysis develops along two lines. In the first, we define income mobility as the growth rate of income over a four-year horizon and we assess its determinants and quantify the degree of convergence between last and first year incomes by means of a 2SLS regression. In the second, we estimate the probability that households move between quintiles of the income distribution from one year to the next and quantify state dependence by employing a dynamic ordered probit model.

Our most original results concerns the reduction of income mobility in the period 2012-2015, as revealed by both the descriptive and econometric analyses. We also find systematic differences in income mobility between the countries analysed, in line with previous work.

Concerning mobility indexes, the Fields and Ok index in 2005-2008 ranges between 0.271 in France and 0.350 in Spain, with Italy and the UK in between with values of 0.287 and 0.330, respectively. The country ranking is comparable to previous findings of the literature. In addition, income movements are mostly due to transfer of incomes from losers (those whose income falls) to gainers rather than due to income growth. These insights remain valid for the period 2012-2015, although mobility decreases for all countries. Similar results hold for Shorrocks' indexes.

By inspecting transition matrices, in both periods we observe a high concentration of individuals staying in the same quintile, especially at the tails of the distribution. However, in the second period, the income distribution turns out to be less mobile for all countries as suggested by the higher percentages of individuals who do not move from their original quintiles compared to the first period. This evidence is in line with the observed reduction in mobility indexes. Moreover, we find that short-distance mobility is much more common than long-distance mobility.

The 2SLS model confirms the finding of lower mobility in the aftermath of the crisis. It further unveils the existence of an income catching-up process in both periods, with evidence of a slower one in the post-crisis period. Income mobility turns out to be positively related to education and the share of workers within the household, while it is negatively affected by the presence of unemployed household members. The role played by education and employment in mitigating the adverse effects of economic shocks may offer policy makers suggestions on the design of appropriate policies to support people's economic standing.

The estimation results of the dynamic ordered probit model reveals the existence of significant state dependence in both periods. Additionally, households at the lower end of the distribution are less likely to move upwards than those lying at the top. However, some period specificities can be detected. In the aftermath of the crisis, compared to the pre-crisis years, it is more challenging for households lying at the bottom of the income distribution to move upwards. Conversely, households lying in the upper part of the distribution do not face this increased difficulty in the post-crisis period, but in fact have an increase in the likelihood of improving their economic standing. Similar to the findings from the 2SLS model, education and a larger share of workers within the household exert a positive effect on the likelihood of households to belong to the upper part of the income distribution.

We are aware that the study of mobility suffers from some limitations because of its double-sided nature. On the one hand, higher income mobility may be viewed as a path to reduce inequalities since individuals in more mobile societies experience more opportunities to move up the income ladder. From this point of view, a society with higher income mobility can perceive income inequalities as more acceptable. On the other hand, higher income mobility may exacerbate income inequalities as it translates into incomes that are more volatile and thus increasing economic insecurity. Dissecting these intricate mechanisms goes beyond the scope of our study and we leave it for future developments of this same work.

Bibliographic references

Aaberge, R., Björklund, A., Jäntti, M., Palme, M., Pedersen, P., Smith, N., Wennemo, T.: Income inequality and income mobility in the Scandinavian countries compared to the United States. *Review of Income and Wealth*, 48, pp. 443-469 (2002)

Alves, N., Martins, C.: Mobility and Income inequality in the European Union and in Portugal. *Banco de Portugal Economics Bulletin*, Summer, pp. 57-70 (2012)

Aristei, D., Perugini, C.: The drivers of income mobility in Europe. *Economic Systems*, 39, pp. 197-224 (2015)

Arulampalam, W., Stewart, M. B.: Simplified implementation of the Heckman estimator of the dynamic probit model and a comparison with alternative estimators. *Oxford Bulletin of Economics and Statistics*, 71, pp. 659-681 (2009)

Ayala, L., Sastre, M.: The structure of income mobility: Empirical evidence from five EU countries. *Empirical Economics*, 35, pp. 451-473 (2008)

Atkinson, A. B., Bourguignon, F., Morrisson, C.: Empirical Studies of Earnings Mobility, Harwood Academic Publishers GmbH (1992)

Bachmann, R., Bechara, P., Schaffner, S.: Wage inequality and wage mobility in Europe. *Review of Income and Wealth*, 62, pp. 181-197 (2016)

Beccaria, L., Maurizio, R., Trombetta, M., Vazquez, G.: Income instability during a period of improving labor and social conditions: Latin America in the 2000s. Annals of the 51st Annual Meeting of the Asociacion Argentina de Economia Politica, November (2016)

Burkhauser, R. V., Couch, K. A.: Intra-generational inequality and intertemporal mobility. In: Salverda, W., Nolan, B., Smeeding, T.M. (eds.) The Oxford Handbook of Economic Inequality, Oxford University Press (2009)

Cantó, O., Ruiz, D. O.: The Contribution of Income Mobility to Economic Insecurity in the US and Spain during the Great Recession. In: Garner, T.I., Short, K.S. (eds.) Measurement of Poverty, Deprivation, and Economic Mobility (Research on Economic Inequality, Vol. 23), Emerald Group Publishing Limited, pp.109-152 (2015)

Cappellari, L.: Earnings mobility among Italian low-paid workers. *Journal of Population Economics*, 20, pp. 465-482 (2007)

Cappellari, L., Jenkins, S. P.: Earnings and labour market volatility in Britain, with a transatlantic comparison. *Labour Economics*, 30, pp. 201-211 (2014)

Carroll, D. R., Chen, A.: Income inequality matters, but mobility is just as important. Economic Commentary no. 2016-06, Federal Reserve Bank of Cleveland (2016)

Chen, W. H.: Cross-national difference in income mobility: Evidence from Canada, the United States, Great Britain and Germany. *Review of Income and Wealth*, 55, pp. 75-100 (2009)

Contoyannis, P., Jones, A. M., Rice, N.: The dynamics of health in the British Household Panel Survey. *Journal of Applied Econometrics*, 19, pp. 473-503 (2004)

Cowell, F. A.: Measures of distributional change: An axiomatic approach. *Review of Economic Studies*, 52, pp. 135-151 (1985)

Cowell, F. A., Flachaire, E.: Measuring Mobility. *Quantitative Economics*, 9, pp. 865-901 (2018)

D'Agostino, M., Dardanoni, V.: The measurement of rank mobility. *Journal of Economic Theory*, 144, pp. 1783-1803 (2009)

Fields, G. S.: Does income mobility equalize longer-term incomes? New measures of an old concept. *Journal of Economic Inequality*, 8, pp. 409-427 (2010)

Fields, G. S., Cichello, P., Freije, S., Sánchez Puerta, M. L.: Household Income Dynamics: A four country study. *Journal of Development Studies*, 40, pp. 30-54 (2003)

Fields, G. S., Duval-Hernández, R., Freije, S., Sánchez Puerta, M. L.: Earnings mobility, inequality, and economic growth in Argentina, Mexico and Venezuela. *Journal of Economic Inequality*, 13, pp. 103-128 (2015)

Fields, G. S., Ok, E.: The Meaning and Measurement of Income Mobility. *Journal of Economic Theory*, 71, pp. 349-377 (1996)

Fields, G. S., Ok, E.: Measuring Movement of Incomes. *Economica*, 66, pp. 455-471 (1999)

Gardiner, K., Hills, J.: Policy implications of new data on income mobility. *The Economic Journal*, 109, pp. 91-111 (1999)

Garnero, A., Hijzen, A., Martin, S.: More Unequal, But More Mobile? Earnings Inequality and Mobility in OECD Countries. *Labour Economics*, 56, pp. 26-35 (2019)

Greene, W., Hensher, D. A.: Modeling ordered choices. A primer. Cambridge University Press (2010)

Heckman, J.: The incidental parameters problem and the problem of initial conditions in estimating a discrete time–discrete data stochastic process. In: Manski, C.F., McFadden, D. (eds.) Structural Analysis of Discrete Data with Econometric Applications, MIT Press, Cambridge, MA, pp. 179-195 (1981)

Jäntti, M., Jenkins, S. P.: Income mobility. In: Atkinson, A.B., Bourguignon, F. (eds.) *Handbook of Income Distribution*, 2, pp. 807-935, Elsevier (2015)

Jarvis, S., Jenkins, S. P.: Low Income Dynamics in 1990s in Britain. Fiscal Studies 18, pp. 123-142 (1997)

Jarvis, S., Jenkins, S. P.: How much income mobility is there in Britain? *The Economic Journal*, 108, pp. 428-443 (1998)

Jenkins, S. P.: Modelling Household Income Dynamics. *Journal of Population Economics*, 13, pp. 529-567 (2000)

Kennedy, S., Yosuke, J., Haugh, D., Lenain, P.: Taxes, income and economic mobility in Ireland: New evidence from tax records data. OECD Economics Department Working Papers, no. 1269, OECD Publishing, Paris (2015)

Lamman, C., Veldhuis, N., Palacios, M., MacIntyre, H.: Measuring Income Mobility in Canada, 2016. Fraser Institute. http://www.fraserinstitute.org (2016)

OECD: The quality of working lives: Earnings mobility, labour market risk and long-term inequality. Employment Outlook, Chapter 4, OECD Publishing, Paris (2015)

Pavlopoulos, D., Muffels, R., Vermunt, J. K.: Wage mobility in Europe. A comparative analysis using restricted multinomial logit regression. *Quality & Quantity*, 44, pp. 115-129 (2010)

Prieto-Rodriguez, J., Rodriguez, J. G., Salas, R.: Income mobility and economic inequality from a regional perspective. *Journal of Applied Economics*, 13, pp. 335-350 (2010)

Rabe-Hesketh, S., Skrondal, S.: Avoiding biased versions of Wooldridge's simple solution to the initial conditions problem. *Economics Letters*, 120, pp. 346-349 (2013)

Raferzeder, T., Winter-Ebmer R.: Who is on the rise in Austria: Wage mobility and mobility risk. *Journal of Economic Inequality*, 5, pp. 39-51 (2007)

Roodman, D.: How to do xtabond2: An introduction to difference and system GMM in Stata. *The Stata Journal*, 9, pp. 86-136 (2009)

Sologon, D., O'Donogue, C.: Increased opportunity to move up the income ladder? Earnings mobility in EU: 1994-2001. IZA Discussion Paper no. 4311 (2009)

Shorrocks, A.: Income Inequality and Income Mobility. *Journal of Economic Theory*, 19, pp. 376-393 (1978a)

Shorrocks, A.: The measurement of mobility. *Econometrica*, 46, pp. 1013-1024 (1978b)

Stewart, M. B., Swaffield, J. K.: Low pay dynamics and transition probabilities. *Economica*, 66, pp. 23-42 (1999)

Van Kerm, P., Pi Alperin, M. N.: Inequality, growth and mobility: The intertemporal distribution of income in European countries 2003-2007. *Economic Modelling*, 35, pp. 931-939 (2013)

Wooldridge, J. M.: Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics*, 20, pp. 39-54 (2005)

TABLES

Table 1 Sample composition (%)

	2005-2008	2012-2015	Overall sample
France	27.6	27.2	27.4
Italy	25.1	23.4	24.2
Spain	19.3	18.6	18.9
UK	28.0	30.9	29.4
Total	100.0	100.0	100.0

Source: own calculations on EU-SILC data. Weighted statistics.

Table 2 Descriptive statistics

	period 1 = 2005 - 2008					**period 2 = 2012 - 2015**				
	mean	sd	min	max	N	mean	sd	min	max	N
Delta log equivalised income	0.032	0.426	-2.364	3.189	8747	0.021	0.399	-3.030	2.612	8644
Log equivalised income *(initial year)*	9.850	0.557	7.087	11.656	8747	9.823	0.554	7.214	11.445	8644
Household head characteristics										
age: 16-34	0.210	0.407	0	1	35508	0.204	0.403	0	1	35360
age: 35-44	0.305	0.460	0	1	35508	0.283	0.450	0	1	35360
age: 45-54	0.265	0.441	0	1	35508	0.276	0.447	0	1	35360
age: 55-64	0.221	0.415	0	1	35508	0.238	0.426	0	1	35360
education: none or primary	0.108	0.310	0	1	35508	0.065	0.247	0	1	35360
education: lower secondary	0.213	0.409	0	1	35508	0.215	0.411	0	1	35360
education: upper secondary	0.387	0.487	0	1	35508	0.375	0.484	0	1	35360
education: tertiary	0.292	0.455	0	1	35508	0.345	0.475	0	1	35360
Female	0.316	0.465	0	1	35508	0.354	0.478	0	1	35360
Married	0.672	0.469	0	1	35508	0.639	0.480	0	1	35360
Household characteristics										
Share of workers	0.465	0.351	0	1	35508	0.475	0.356	0	1	35360
Share of unemployed	0.022	0.120	0	1	35508	0.043	0.166	0	1	35360
Share of pensioners	0.050	0.197	0	1	35508	0.037	0.170	0	1	35360
Share of adults	0.850	0.212	0.167	1	35508	0.849	0.215	0.143	1	35360

Source: own calculations on EU-SILC data. Weighted statistics.

Table 3 Income mobility indexes

	France	Italy	Spain	UK
		period 1 = 2005-2008		
FO (t, t+3)	0.271	0.287	0.350	0.330
transfer component	0.144	0.248	0.264	0.225
growth component	0.127	0.039	0.086	-0.104
Shorrocks M: all transitions				
Mean log deviation - GE(0)	0.221	0.205	0.264	0.232
Theil - GE(1)	0.218	0.192	0.230	0.213
Sq. coefficient of variation - GE(2)	0.234	0.206	0.227	0.219
Gini	0.108	0.094	0.116	0.107
		period 2 = 2012-2015		
FO (t, t+3)	0.230	0.279	0.304	0.297
transfer component	0.195	0.271	0.229	0.209
growth component	0.035	-0.008	-0.075	0.088
Shorrocks M: all transitions				
Mean log deviation - GE(0)	0.168	0.179	0.159	0.186
Theil - GE(1)	0.164	0.163	0.120	0.171
Sq. coefficient of variation - GE(2)	0.177	0.179	0.109	0.175
Gini	0.081	0.077	0.055	0.086

Source: own calculations on EU-SILC data. Weighted statistics.

Table 4 Transition matrices (%)

(a) France: 2005-2008

	quintile (t)					
quintile (t-1)	1	2	3	4	5	Total
1	66.8	20.3	6.5	3.6	2.9	100
2	22.3	47.2	20.4	6.4	3.6	100
3	6.1	24.8	45.7	18.0	5.4	100
4	2.6	5.8	20.6	53.7	17.2	100
5	2.6	2.8	6.0	18.2	70.4	100
Total	20.3	20.3	19.7	19.8	19.9	100

(b) France: 2012-2015

	quintile (t)					
quintile (t-1)	1	2	3	4	5	Total
1	73.2	18.0	5.1	2.2	1.3	100
2	19.2	54.7	18.0	5.7	2.3	100
3	4.8	20.3	53.5	17.1	4.2	100
4	2.4	5.2	19.2	56.3	16.9	100
5	1.5	2.0	4.6	17.6	74.3	100
Total	20.8	20.3	20.1	19.5	19.4	100

(c) Italy: 2005-2008

	quintile					
quintile (t-1)	1	2	3	4	5	Total
1	70.0	20.6	6.1	2.1	1.3	100
2	19.7	50.6	20.0	7.0	2.7	100
3	6.3	18.2	47.5	20.3	7.7	100
4	2.3	7.0	21.0	50.4	19.3	100
5	1.8	3.2	6.8	20.3	68.0	100
Total	19.5	19.7	20.4	20.2	20.1	100

(d) Italy: 2012-2015

	quintile (t)					
quintile (t-1)	1	2	3	4	5	Total
1	72.6	20.9	3.9	1.7	0.9	100
2	17.8	56.3	18.9	5.3	1.6	100
3	4.8	16.2	53.1	20.4	5.5	100
4	2.0	5.0	17.5	57.9	17.6	100
5	1.2	2.1	6.7	16.3	73.7	100
Total	18.6	19.6	20.2	21.1	20.5	100

(e) Spain: 2005-2008

	quintile (t)					
quintile (t-1)	1	2	3	4	5	Total
1	61.4	22.1	10.3	4.7	1.4	100
2	27.5	39.0	22.2	8.6	2.7	100
3	9.1	27.8	35.7	21.4	6.0	100
4	3.8	9.1	25.6	40.9	20.5	100
5	1.9	2.3	6.1	21.1	68.5	100
Total	21.0	19.9	19.8	19.2	20.0	100

(f) Spain: 2012-2015

	quintile (t)					
quintile (t-1)	1	2	3	4	5	Total
1	70.5	24.1	3.2	1.6	0.7	100
2	21.1	55.6	18.5	4.3	0.4	100
3	4.9	18.0	56.5	17.7	2.9	100
4	1.7	3.7	16.6	63.2	14.8	100
5	0.6	1.3	3.8	13.1	81.2	100
Total	18.7	20.1	19.9	20.6	20.7	100

Table 4 Transition matrices (%) (cont.)

(g) UK: 2005-2008

	quintile (t)					
quintile (t-1)	1	2	3	4	5	Total
1	67.2	18.6	7.5	4.0	2.7	100
2	21.6	47.1	21.3	7.2	2.7	100
3	8.6	23.9	40.8	19.7	6.9	100
4	4.5	9.9	22.5	48.1	15.0	100
5	2.2	3.0	4.9	16.2	73.6	100
Total	22.1	20.8	19.0	18.2	19.8	100

(h) UK: 2012-2015

	quintile (t)					
quintile	1	2	3	4	5	Total
1	63.7	24.2	6.8	4.2	1.1	100
2	25.2	48.6	18.2	5.7	2.2	100
3	7.3	21.1	45.4	20.9	5.3	100
4	4.9	5.5	23.8	48.4	17.3	100
5	1.8	2.8	4.9	17.1	73.4	100
Total	21.7	21.0	19.5	18.6	19.1	100

Source: own calculations on EU-SILC data.

Table 5 Two-stage least squares: Estimated coefficients

	(1) Pooling		(2) Pooling with interactions		(3) Period 1		(4) Period 2	
	coeff.	robust s.e.	coeff.	robust s.e.	coeff.	robust s.e.	coeff.	robust s.e.
Initial year income								
log of equivalised income	-0.238	0.038 ***	-0.169	0.042 ***	-0.235	0.061 ***	-0.110	0.058 *
Household-head characteristics (initial year)								
age: 16-34	0.032	0.012 ***	0.031	0.012 ***	0.002	0.016	0.061	0.017 ***
age: 45-54	0.021	0.010 **	0.019	0.010 **	0.025	0.013 *	0.017	0.014
age: 55-64	0.022	0.012 *	0.018	0.012	0.032	0.018 *	0.007	0.017
education: None or primary	0.008	0.015	0.008	0.015	0.000	0.020	0.016	0.023
education: upper secondary	0.046	0.012 ***	0.044	0.012 ***	0.060	0.017 ***	0.029	0.016 *
education: tertiary	0.106	0.017 ***	0.092	0.018 ***	0.119	0.024 ***	0.063	0.026 **
female	-0.009	0.008	0.002	0.008	-0.006	0.012	0.011	0.012
married	0.000	0.010	-0.010	0.01	-0.013	0.014	-0.004	0.015
Household characteristics (initial year)								
share of employed	0.106	0.023 ***	0.067	0.025 ***	0.077	0.037 **	0.066	0.035 *
share of unemployed	-0.250	0.04 ***	-0.213	0.041 ***	-0.196	0.066 ***	-0.199	0.053 ***
share of pensioners	0.061	0.027 **	0.031	0.028	0.020	0.037	0.044	0.043
Household characteristics (delta)								
share of employed	0.209	0.02 ***	0.200	0.021 ***	0.177	0.028 ***	0.231	0.031 ***
share of unemployed	-0.140	0.038 ***	-0.119	0.039 ***	-0.131	0.060 **	-0.089	0.052 *
share of pensioners	0.052	0.03 *	0.036	0.031	0.007	0.043	0.072	0.043 *
share of adults	0.145	0.034 ***	0.153	0.034 ***	0.190	0.048 ***	0.105	0.049 **
Post crisis								
2012 dummy	-0.005	0.008	-0.138	0.019 ***				
Country dummies								
France	0.132	0.014 ***	0.078	0.019 ***	0.098	0.022 ***	0.131	0.020 ***
Spain	0.055	0.014 ***	-0.013	0.02	0.006	0.024	0.083	0.018 ***
UK	0.081	0.020 ***	-0.106	0.03 ***	-0.068	0.039 *	0.181	0.023 ***
France * 2012 dummy			0.071	0.021 ***				
Spain * 2012 dummy			0.106	0.024 ***				
UK * 2012 dummy			0.308	0.029 ***				
constant	2.181	0.350 ***	1.619	0.379 ***	2.237	0.555 ***	0.918	0.531 *
Wu-Hausman endogeneity test Chi-sq(1)		30.229 [0.000]		44.899 [0.000]		14.86 [0.000]		31.402 [0.000]
Test of excluded instruments	F(1, 17370)	452.17 [0.000]	F(1, 17367)	389.51 [0.000]	F(1, 8727)	189.17 [0.000]	F(1, 8624)	197.22 [0.000]
Underidentification test:								
Kleibergen-Paap statistic		403.99 [0.000]		349.54 [0.000]		175.17 [0.000]		171.46 [0.000]
N. observations		17391		17391		8747		8644
R-sq		0.224		0.205		0.250		0.160

*Source: own calculations on EU-SILC data. Estimates are weighted. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

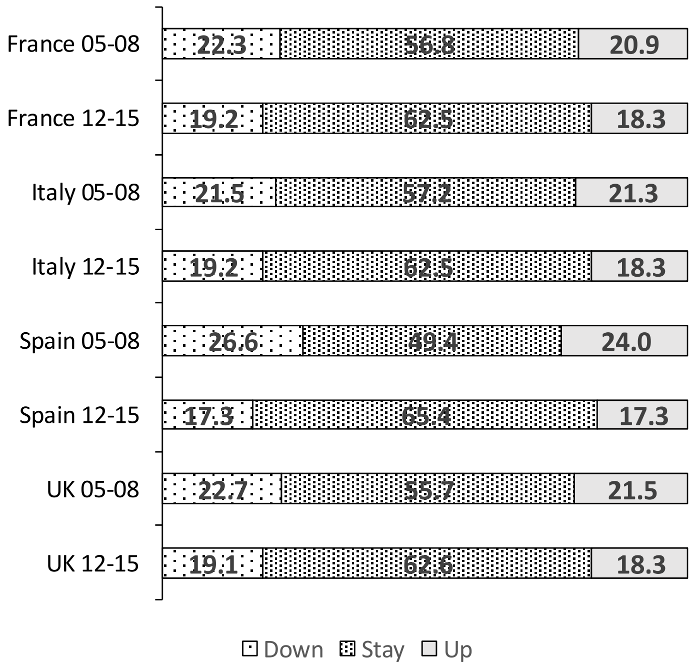
Table 6 Dynamic ordered probit model: Average partial effects (outcome 5)

	(1) Pooling			(2) Pooling with interactions			(3) Period 1			(4) Period 2		
	coeff.	robust s.e.		coeff.	robust s.e.		coeff.	robust s.e.		coeff.	robust s.e.	
Quintile (lag)												
1st	-0.056	0.005	***	-0.055	0.005	***	-0.049	0.008	***	-0.062	0.007	***
2nd	-0.032	0.004	***	-0.032	0.004	***	-0.026	0.005	***	-0.040	0.005	***
4th	0.029	0.004	***	0.029	0.004	***	0.029	0.006	***	0.031	0.006	***
5th	0.092	0.008	***	0.092	0.008	***	0.089	0.011	***	0.099	0.012	***
Household head characteristics (lag)												
age: 16-34	0.000	0.004		0.000	0.004		-0.006	0.005		0.005	0.006	
age: 45-54	0.011	0.003	***	0.011	0.003	***	0.016	0.005	***	0.006	0.004	
age: 55-64	0.025	0.004	***	0.025	0.004	***	0.035	0.006	***	0.016	0.005	***
education: none or primary	-0.015	0.004	***	-0.015	0.004	***	-0.020	0.006	***	-0.008	0.006	
education: upper secondary	0.022	0.003	***	0.023	0.003	***	0.027	0.005	***	0.018	0.005	***
education: tertiary	0.073	0.004	***	0.073	0.004	***	0.080	0.006	***	0.064	0.006	***
female	-0.001	0.003		-0.001	0.003		-0.001	0.005		-0.002	0.004	
married	-0.010	0.008		-0.010	0.008		-0.005	0.013		-0.016	0.010	
Household characteristics (lag)												
Share of employed	0.043	0.008	***	0.043	0.008	***	0.049	0.011	***	0.036	0.013	***
Share of unemployed	-0.018	0.015		-0.018	0.015		-0.029	0.024		-0.016	0.020	
Share of pensioners	-0.008	0.013		-0.008	0.013		-0.006	0.018		-0.010	0.018	
Post crisis dummy												
Post	-0.001	0.003		-0.004	0.005							
Country dummies												
France	-0.020	0.003	***	-0.018	0.004	***	-0.021	0.005	***	-0.020	0.005	***
Spain	0.004	0.004		-0.005	0.006		-0.003	0.007		0.011	0.005	**
UK	-0.026	0.004	***	-0.028	0.006	***	-0.032	0.006	***	-0.022	0.006	***
France * post				-0.004	0.006							
Spain * post				0.018	0.008	**						
UK * post				0.004	0.008							

*Source: own calculations on EU-SILC data. Estimates are weighted. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

FIGURES

Figure 1 Upward and downward mobility

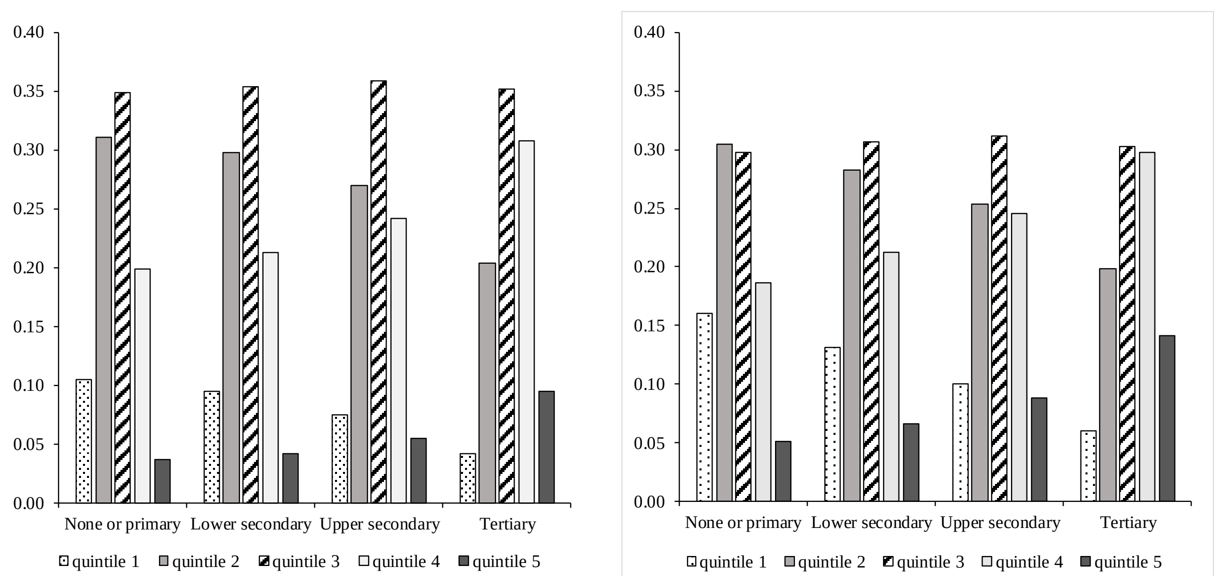


Source: own calculations on EU-SILC data.

Figure 2 Predicted probabilities by education level

(a) period 1 = 2005-2008

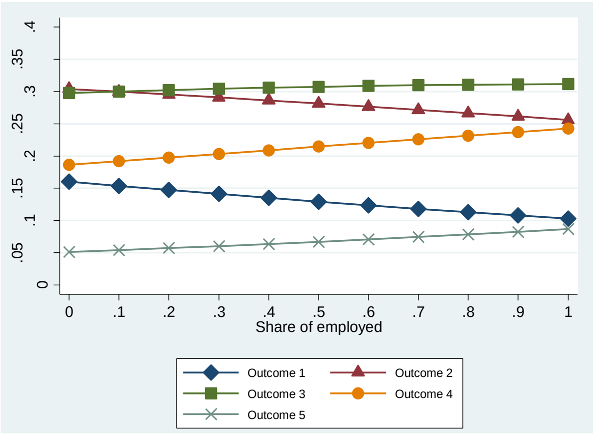
(b) period 2 = 2012-2015



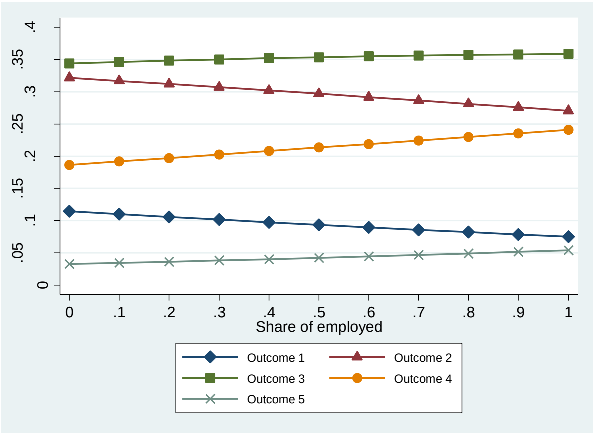
Source: own calculations on EU-SILC data.

Figure 3 Predicted probabilities by share of employed household members

(a) period 1 = 2005-2008



(b) period 2 = 2012-2015



Source: own calculations on EU-SILC data.

APPENDIX

Table A1 Two-stage least squares: First stage regression

	(1) Pooling			(2) Pooling with interactions			(3) Period 1			(4) Period 2		
	coeff.	robust s.e.		coeff.	robust s.e.		coeff.	robust s.e.		coeff.	robust s.e.	
Instrumental variable (initial year)												
Asset ownership	0.217	0.010	***	0.206	0.010	***	0.184	0.013	***	0.230	0.016	***
Household-head characteristics (initial year)												
age: 16-34	-0.066	0.014	***	-0.062	0.014	***	-0.065	0.017	***	-0.060	0.022	***
age: 45-54	0.017	0.012		0.018	0.011		0.024	0.016		0.011	0.017	
age: 55-64	0.081	0.015	***	0.079	0.015	***	0.084	0.021	***	0.075	0.021	***
education: None or primary	-0.081	0.018	***	-0.079	0.018	***	-0.076	0.023	***	-0.081	0.028	***
education: upper secondary	0.116	0.012	***	0.112	0.012	***	0.128	0.016	***	0.096	0.018	***
education: tertiary	0.298	0.014	***	0.292	0.014	***	0.290	0.018	***	0.293	0.020	***
female	-0.026	0.010	**	-0.032	0.010	***	-0.023	0.013	*	-0.041	0.015	***
married	0.098	0.011	***	0.101	0.011	***	0.101	0.014	***	0.101	0.016	***
Household characteristics (initial year)												
share of employed	0.450	0.018	***	0.456	0.018	***	0.493	0.022	***	0.418	0.027	***
share of unemployed	-0.204	0.045	***	-0.215	0.045	***	-0.129	0.073	*	-0.270	0.057	***
share of pensioners	0.270	0.034	***	0.280	0.035	***	0.274	0.046	***	0.294	0.053	***
Household characteristics (delta)												
share of employed	0.096	0.024	***	0.098	0.024	***	0.117	0.030	***	0.081	0.038	**
share of unemployed	-0.092	0.047	**	-0.101	0.047	**	-0.030	0.070		-0.145	0.061	**
share of pensioners	0.165	0.032	***	0.167	0.032	***	0.156	0.044	***	0.183	0.047	***
share of adults	-0.260	0.037	***	-0.254	0.036	***	-0.262	0.052	***	-0.248	0.051	***
Post crisis												
2012 dummy	-0.066	0.009	***	0.003	0.025							
Country dummies												
France	0.171	0.014	***	0.169	0.018	***	0.173	0.019	***	0.179	0.021	***
Spain	0.211	0.015	***	0.242	0.019	***	0.245	0.019	***	0.184	0.023	***
UK	0.426	0.016	***	0.527	0.021	***	0.527	0.021	***	0.335	0.025	***
France * 2012 dummy				0.016	0.028							
Spain * 2012 dummy				-0.061	0.030	**						
UK * 2012 dummy				-0.197	0.032	***						
constant	9.108	0.019	***	9.078	0.022	***	9.058	0.026	***	9.098	0.028	***
N. observations		17391			17391			8747			8644	

*Source: own calculations on EU-SILC data. Estimates are weighted. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

Table A2 Dynamic ordered probit model: Estimated coefficients

	(1) Pooling			(2) Pooling with interactions			(3) Period 1			(4) Period 2		
	coeff.	robust s.e.		coeff.	robust s.e.		coeff.	robust s.e.		coeff.	robust s.e.	
Quintile (lag)												
1st	-0.476	0.047	***	-0.475	0.047	***	-0.377	0.064	***	-0.612	0.071	***
2nd	-0.262	0.030	***	-0.262	0.030	***	-0.191	0.038	***	-0.366	0.047	***
4th	0.208	0.029	***	0.208	0.029	***	0.189	0.038	***	0.242	0.045	***
5th	0.604	0.046	***	0.605	0.046	***	0.542	0.060	***	0.705	0.071	***
Household head characteristics (lag)												
age: 16-34	-0.001	0.030		-0.000	0.030		-0.045	0.038		0.043	0.048	
age: 45-54	0.082	0.026	***	0.082	0.026	***	0.111	0.035	***	0.052	0.038	
age: 55-64	0.192	0.031	***	0.193	0.031	***	0.241	0.044	***	0.140	0.045	***
education: None or primary	-0.133	0.039	***	-0.130	0.039	***	-0.163	0.050	***	-0.080	0.060	
education: upper secondary	0.181	0.028	***	0.182	0.028	***	0.198	0.036	***	0.164	0.044	***
education: tertiary	0.546	0.033	***	0.547	0.033	***	0.547	0.042	***	0.541	0.053	***
female	-0.006	0.025		-0.011	0.024		-0.008	0.033		-0.014	0.037	
married	-0.079	0.064		-0.078	0.064		-0.036	0.093		-0.135	0.087	
Household characteristics (lag)												
Share of employed	0.332	0.066	***	0.333	0.066	***	0.344	0.080	***	0.310	0.110	***
Share of unemployed	-0.139	0.117		-0.139	0.117		-0.205	0.169		-0.135	0.171	
Share of pensioners	-0.061	0.100		-0.061	0.100		-0.042	0.131		-0.086	0.154	
Post crisis dummy												
Post	-0.008	0.022		-0.035	0.038							
Country dummies												
France	-0.157	0.026	***	-0.142	0.034	***	-0.144	0.033	***	-0.171	0.040	***
Spain	0.027	0.032		-0.038	0.047		-0.021	0.045		0.094	0.045	**
UK	-0.204	0.034	***	-0.219	0.045	***	-0.227	0.044	***	-0.190	0.052	***
France * post				-0.028	0.049							
Spain * post				0.136	0.062	**						
UK * post				0.031	0.065							

Table A2 Dynamic ordered probit model: Estimated coefficients (cont.)

	(1) Pooling			(2) Pooling with interactions			(3) Period 1			(4) Period 2		
	coeff.	robust s.e.		coeff.	robust s.e.		coeff.	robust s.e.		coeff.	robust s.e.	
Initial quintile												
1st	-1.312	0.055	***	-1.310	0.055	***	-1.245	0.073	***	-1.372	0.084	***
2nd	-0.551	0.039	***	-0.550	0.039	***	-0.550	0.049	***	-0.543	0.062	***
4th	0.640	0.038	***	0.640	0.038	***	0.543	0.049	***	0.757	0.058	***
5th	1.627	0.060	***	1.628	0.060	***	1.448	0.075	***	1.842	0.100	***
Estimated cut points												
Cut1	-1.002	0.052	***	-1.015	0.053	***	-0.894	0.066	***	-1.142	0.079	***
Cut2	0.239	0.051	***	0.225	0.052	***	0.250	0.064	***	0.222	0.078	***
Cut3	1.343	0.053	***	1.330	0.054	***	1.266	0.067	***	1.445	0.082	***
Cut4	2.608	0.060	***	2.594	0.061	***	2.431	0.075	***	2.843	0.094	***
sigma2_u	0.655	0.040	***	0.654	0.040	***	0.601	0.050	***	0.714	0.064	***
Number of observations	52173			52173			26241			25932		
Number of households	17391			17391			8747			8644		
Log likelihood value	-4.09E+08			-4.09E+08			-2.16E+08			-1.91E+08		
Test of joint significance	chi2(df)	pvalue		chi2(df)	pvalue		chi2(df)	pvalue		chi2(df)	pvalue	
time averages	135.45(4)	0.000		137.00(4)	0.000		52.00(4)	0.000		87.67(4)	0.000	
initial values and time averages	1253.07(8)	0.000		1255.56(8)	0.000		641.52(8)	0.000		609.45(8)	0.000	
quintile (lag), initial values and time av	5538.36(12)	0.000		5549.46(12)	0.000		2777.58(12)	0.000		2909.22(12)	0.000	

*Source: own calculations on EU-SILC data. Estimates are weighted. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

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